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Spatial Analysis of Population Dynamics in Fukushima Prefecture: During the Post-Disaster Recovery Process and Estimation Using GMM

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Abstract

This study analyzed post-disaster population changes in Fukushima Prefecture from 2010 to 2020, using spatial analysis and econometric methods. Significant population decline occurred, particularly in designated evacuation zones, between 2010 and 2015. While some population recovery was seen in these areas after evacuation orders were lifted (2015-2020), overall levels remained substantially below 2010 figures. Widespread aging was also noted across the prefecture, often distinct from disaster impacts. Econometric findings showed that increasing average age had a negative effect on population. Crucially, indicators of social infrastructure, specifically the number of high schools and hospitals, were positively associated with population levels, suggesting they aid retention. Municipal fiscal capacity did not show a significant relationship with population changes. The study highlights ongoing challenges for social inclusion and suggests infrastructure investment is vital for revitalization.

Introduction

Social inclusion is generally understood as a concept that focuses on communities, groups, and individuals, examining the extent and quality of their participation in and access to the fundamental functions and relationships of society (Alex, 2015). In contemporary Japan, a rapid population decline and accelerated aging are projected in the coming decades (Development Bank of Japan, 2015), increasing the risk of isolation and exclusion among vulnerable groups and minorities. This underscores the necessity of strategic responses tailored to the distinct demographic structures and social contexts of each region in order to achieve social inclusion. Building an inclusive society is therefore considered a critical policy challenge.

In this study, Fukushima Prefecture was selected as a focal case for empirical investigation into the construction of an inclusive society. Since the Great East Japan Earthquake and the accident at the Fukushima Daiichi Nuclear Power Plant in 2011, Fukushima has experienced a dramatic outflow of population and a fragmentation of its local communities. Outmigration has been especially prominent among the younger and child-rearing populations, leading to a rapid rise in the aging rate. While return policies have been promoted as part of regional recovery efforts, certain areas remain designated as difficult-to-return zones with continued restrictions on residence. Consequently, the challenge of achieving social inclusion in regional revitalization remains acute.

In this fiscal year, as a preliminary step in our analysis, we conducted a review of prior research, developed a GIS-based population dynamics database, and carried out econometric analyses. Based on these efforts, we explored the challenges of social inclusion in disaster-affected areas, with a particular focus on the demographic realities revealed through spatial population trends.

Studies on Social Inclusion in the Context of the Fukushima Disaster

In Fukushima Prefecture, the Great East Japan Earthquake and the accident at the Fukushima Daiichi Nuclear Power Plant in 2011 had a profoundly serious impact on local communities. These events have significantly influenced demographic trends, particularly accelerating population outflow and depopulation (Abe, 2015). Following the disaster, a large number of people, especially young and child-rearing households, relocated outside the region due to the designation of wide areas as evacuation zones. In some areas, residents have continued to face long-term restrictions on returning (Tanaka, 2019). These conditions have exacerbated pre-existing trends of aging and population decline, threatening the sustainability of local communities and raising concerns about social isolation, infrastructure deterioration, and the hollowing-out of community functions.

Endo et al. (2014) conducted a survey among residents who were forced to relocate to temporary housing from evacuation-designated areas. They reported not only the difficulties of life in temporary housing but also the complexity of decision-making regarding return. Notably, about 30% of respondents in 2013 stated that they "would like to return but are undecided," highlighting how prolonged evacuation and uncertainty about the future seriously affect residents' willingness to return. According to Tanaka (2019), prolonged displacement reduces residents' desire to return and hinders the rebuilding of local social relationships, ultimately slowing actual return behavior. In areas where evacuation orders were lifted within 3.5 years, more than 50% of households had returned. In contrast, in areas where the orders remained for over 5 years, the return rate was still around 10% even 2.5 years after the lifting, indicating a substantial difference. This suggests that the temporal dimension is a critical factor in recovery policy. In addition to decontamination progress, policy responses must also address residents' intentions and the loss of social ties.

Another key institutional issue related to the Fukushima accident is the compensation scheme for affected individuals. In particular, the compensation payments designed and implemented primarily by the national government and TEPCO have been positioned as a foundational means of supporting both individual livelihood recovery and regional reconstruction (TEPCO Holdings, 2021). This scheme is based on the Act on Compensation for Nuclear Damage and has raised policy and legal debates concerning funding and the scope of compensation (Kubo, 2011; Sawa et al., 2012)[1].

Economic compensation plays a critical role in disaster recovery, but determining the appropriate amount and scope of compensation is highly challenging. Several studies report that the compensation process itself may generate perceptions of unfairness, foster social comparison and division, and negatively affect mental health (Brooks et al., 2024). Moreover, even when monetary compensation is provided, it can only partially substitute for non-economic losses and burdens. Critics argue that economic means cannot adequately address the loss of non-material values and resources (Tanaka, 2016; Teranishi, 2016; Yokemoto, 2015). Nevertheless, Endo et al. (2014) found that, in practice, many affected residents ultimately expressed the strongest desire for monetary compensation. This reflects the inherent difficulty of designing and implementing effective compensation policies in disaster contexts.

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[1] According to a 2013 report by the Ministry of Education, Culture, Sports, Science and Technology, the average compensation paid by TEPCO to a model household of four in the difficult-to-return zones was ¥48.3 million (excluding property other than household belongings). Furthermore, as of March 2024, the total amount of compensation required had reached ¥13.4179 trillion (TEPCO Holdings, 2021).

Construction for Spatial/Statistical Data and Methods of Statistical Analysis

This study aims to quantitatively capture the socioeconomic changes in Fukushima Prefecture following the Great East Japan Earthquake by constructing spatial data on demographic changes from 2010 to 2020 and conducting analyses using spatial statistics and econometric methods. Specifically, an annual municipality-level dataset was developed by integrating data from the Resident Registration Migration Report (Statistics Bureau of Japan, 2025), the Population Census (Statistics Bureau of Japan, 2025), and the National Land Numerical Information (National Spatial Planning and Regional Policy Bureau, MLIT, 2025), with added spatial attributes. Key demographic variables analyzed include population density, in-migration and out-migration, aging rate, and mortality rate. For spatial data processing and computation of spatial statistics, ArcGIS Pro 10.8 (Esri, Inc., 2024) was used.

The utility of incorporating geographical context in demographic analysis has been widely reported in prior studies. For example, Pregi et al. (2024) analyzed municipality-level migration data in Slovakia using Global Moran's I and Getis-Ord Gi* statistics, demonstrating that population movement is not spatially random but tends to concentrate in specific areas. This indicates the effectiveness of spatial statistics in capturing the spatial structure of population mobility. Tamura et al. (2017), using 500-meter mesh population data across Japan, found a significant positive spatial autocorrelation between population growth rates and the population density of neighboring areas. Their study suggests the utility of spatially explicit models in explaining broad demographic patterns that conventional gravity models may fail to capture. Demographic indicators such as population density and migration flows are thus expected to show statistical correlations among geographically proximate areas.

Based on these insights, the present study examined post-disaster population changes in Fukushima by integrating spatial statistical analysis with dynamic panel econometrics. Focusing on local spatial autocorrelation, the study employed the Getis-Ord Gi* statistic (Ord and Getis, 1995) to detect localized clusters of population increase or decline across contiguous municipalities. This allowed for the visualization and quantification of spatial clustering in population dynamics—namely, the identification of demographic hotspots and coldspots—thus enabling the identification of geographically continuous patterns of demographic concentration. The Gi* statistics are defined as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij} X_j - \bar{X} \sum_{j=1}^{n} w_{ij}}{S \sqrt{\frac{\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)}{n-1}}}$$

Here, w_{ij} represents the spatial weight matrix, which assigns values based on spatial proximity between municipalities i and j. It is defined either as the inverse of the distance between the two municipalities or as 1 if the two municipalities fall within a defined threshold distance, and 0 otherwise. In this study, the spatial weight matrix assigns a value of 1 if the distance between two municipalities is within the average nearest neighbor distance, and 0 otherwise. The average nearest neighbor's distance is calculated as the mean distance between the centroid of each municipality and its nearest neighbor across all municipalities. Municipalities whose distance from their nearest neighbor exceeds the average by more than three standard deviations are treated as spatial outliers and excluded from the calculation. X_j denotes the variable of interest for municipality j, such as population density. S represents the standard deviation, and n the sample size.

The Gi* statistic is standardized so that, under the null hypothesis of no spatial autocorrelation, it follows a normal distribution. Therefore, it allows for hypothesis testing using Z-values. A positive Gi* value indicates significant positive spatial autocorrelation among high values (i.e., a hotspot), whereas a negative Gi* value indicates significant positive spatial autocorrelation among low values (i.e., a cold spot). Based on these results, we can identify statistically significant clusters of municipalities with high population density (hotspots) and those with low population density (cold spots). In this study, we calculated these values using the Optimized Hot Spot Analysis tool in ArcGIS Pro (Esri, Inc., 2023).

Finally, we conducted a quantitative analysis using panel data from 2010 to 2020 at the municipality level to examine the relationship between population change and other statistical indicators. For this econometric analysis, we employed a dynamic Generalized Method of Moments (GMM) estimator using lagged population as an explanatory variable, allowing us to account for temporal dynamics.

The methodological contribution of this study lies in applying localized hotspot analysis that incorporates spatial autocorrelation, thereby revealing interdependencies and spatial patterns across regions that would likely be overlooked in non-spatial models. Spatial statistical analysis is not merely a visual aid; it offers a theoretical and empirical framework to understand how geographic proximity structurally affects demographic dynamics. As such, it holds practical implications for post-disaster regional reconstruction and policy formulation.

Analysis of Demographic Dynamics and Spatial Distribution

Figure 1 presents the population density of municipalities (per $0.1km^2$) in Fukushima Prefecture from 2010 to 2020, based on the Population Census rather than the Resident Registration Migration Report. In the figure, the yellow dot indicates the location of the Fukushima Prefectural Government, and the red dot indicates the Fukushima nuclear power plant (with the northernmost plant being Fukushima Daiichi).

Unlike the Resident Registration data, which is based on reported residential addresses in the official registry, the Population Census is based on where people were actually living at the time of the survey, as reported in questionnaires. While the Resident Registration allows tracking of migration by recording the origin and destination municipalities, it cannot capture changes if evacuees did not officially update their residence, even if their area was under an evacuation order during the observation period. In cases like this, where sudden large-scale population movements occurred without administrative procedures due to disaster-related evacuation, it is necessary to supplement registry data with survey-based sources like the Population Census, despite limitations such as lower frequency of data collection.

As of 2010, the mountainous southwestern areas were already experiencing low population density and progressing depopulation. While depopulation continued in these rural areas, significant declines in population density were also observed—statistically and visibly—around the Fukushima Daiichi Nuclear Power Plant and in the northwestern area by 2015 and 2020. Notably, in 2015, data could not be obtained for several municipalities designated as evacuation or difficult-to-return zones at that time, including Namie, Futaba, Okuma, and Tomioka (see Figure 2). Even in 2020, no official population data were available for Futaba, where the nuclear power plant is located.

The evacuation zones covered a wide range of coastal municipalities. The timing of evacuation order lifts varied by region, with the earliest being in April 2014 for Tamura City—three years after the disaster. In the figure, evacuation orders were lifted in parts of Tomioka, Okuma, and Futaba in March 2020. The full evacuation order for all of Futaba was not lifted until August 30, 2022, under the Special Measures Act for the Reconstruction and Revitalization of Fukushima (Futaba Town, 2022). These areas required more than eight years before restrictions were removed. As Tanaka (2019) notes, regions with long-term evacuation orders have seen persistently low return rates, suggesting that prolonged restrictions significantly influence residents' decisions about returning. These findings indicate the need for not only physical infrastructure reconstruction but also comprehensive recovery policies that address social and psychological dimensions.

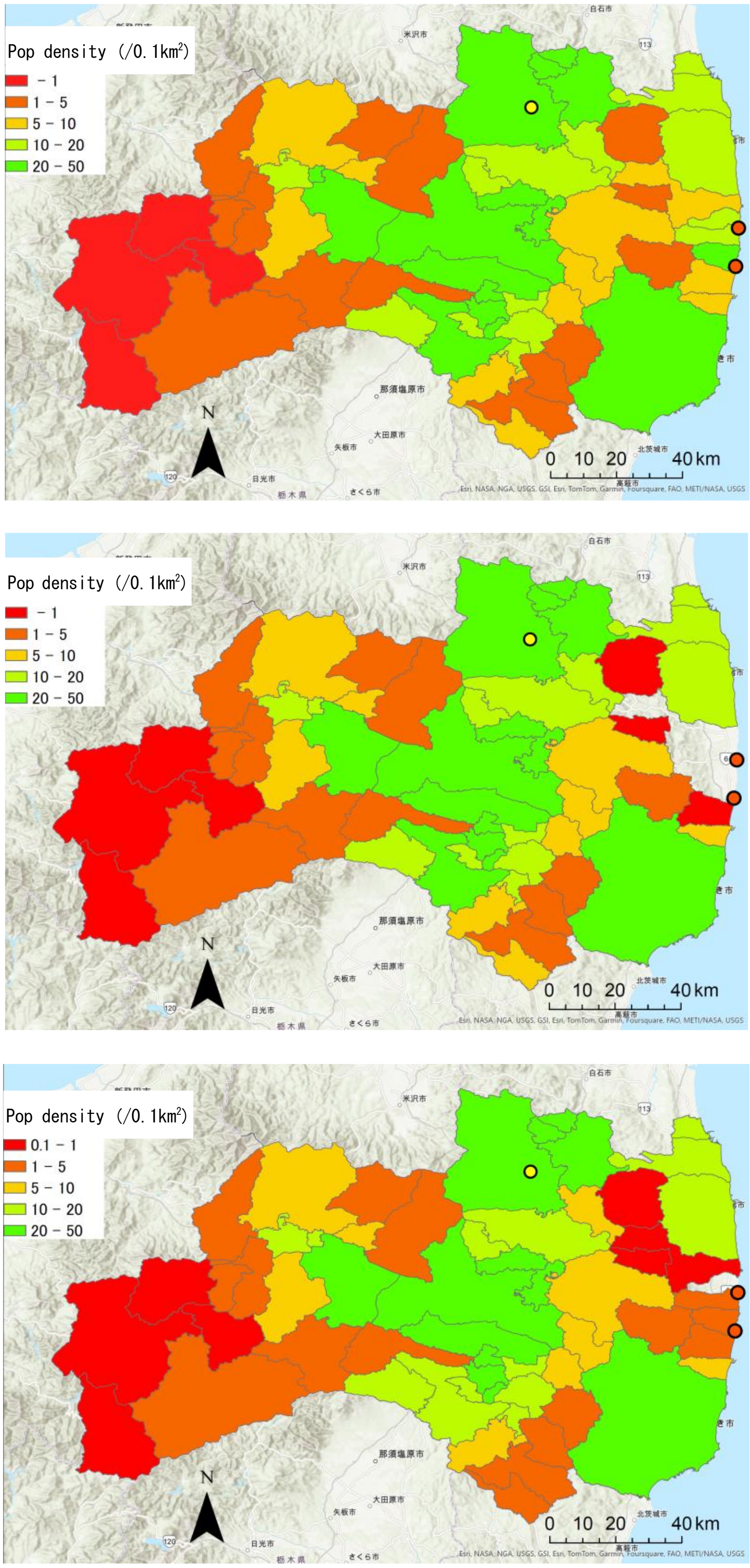

Figure 1. Population Density (2010–2020)

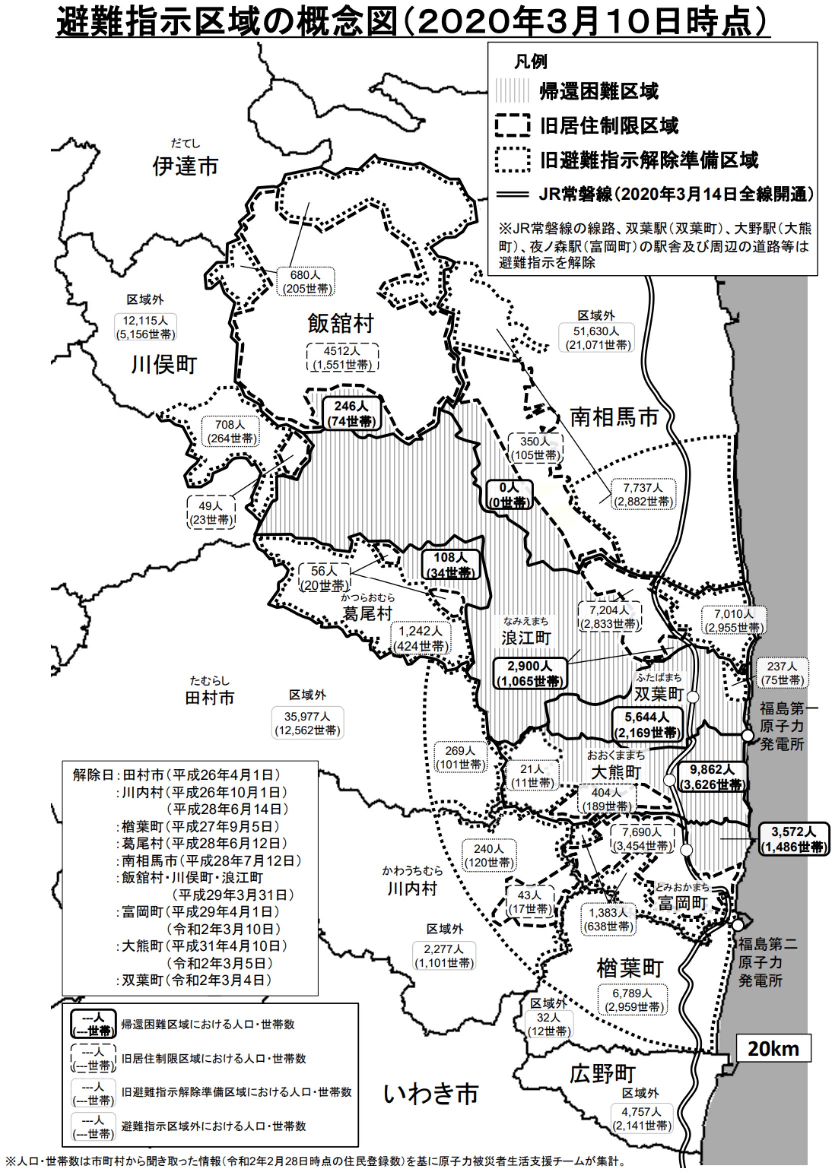

Figure 2. Evacuation Zones and Population/Number of Households by Area (Source: Ministry of Economy, Trade and Industry, 2020)

Next, Figure 3 illustrates the spatial distribution of ambient radiation dose rates measured at one meter above ground level as of April 2011, based on data released by the Japan Atomic Energy Agency (2018). The red lines in the figure indicate municipal boundaries. In the figure, darker red areas indicate higher radiation levels. Elevated dose rates are observed around the Fukushima Daiichi Nuclear Power Plant and extend northwest from the plant. The distribution also stretches southwest along the flatlands (Nakadori region) between the surrounding mountain ranges and the Abukuma Highlands. In contrast, areas west of Fukushima City are largely shielded by the Ou Mountains, resulting in significantly lower dose rates across nearly the entire region.

This figure visually captures the geographic unevenness of radiation levels observed immediately after the Fukushima Daiichi accident. It serves as important reference material for understanding the spatial consistency between radiation dispersion and the evacuation zones that were designated in response. These evacuation orders may have played a significant role in shaping subsequent demographic changes in the affected areas.

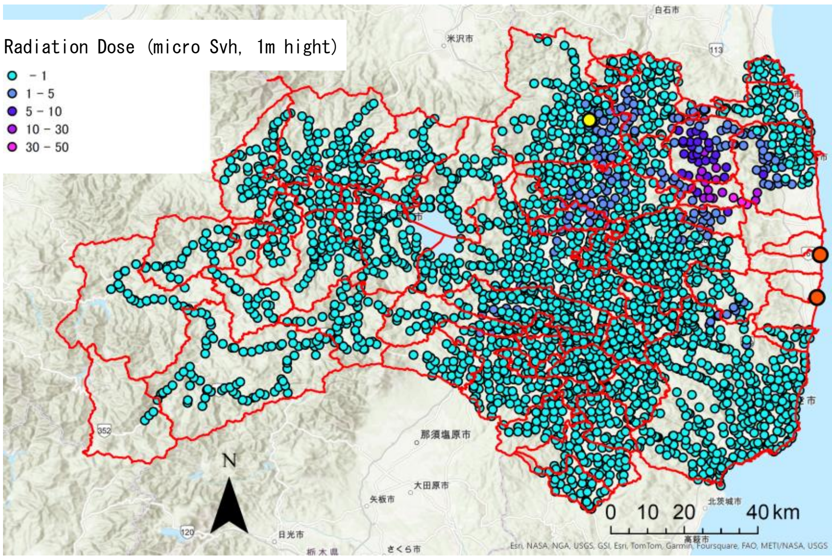

Figure 3. Spatial Distribution of Ambient Radiation Dose Rates (as of April 2011, Source: Japan Atomic Energy Agency [2018]; created by the authors based on mesh survey data from Fukushima Prefecture's Environmental Radiation Monitoring)

Figure 4 shows changes in population based on Population Census data, while Figure 5 presents the results of a hotspot analysis on population change rates. As seen in Figure 4, from 2010 to 2015, significant population decline is observed in and around the evacuation zones. Municipalities showing particularly notable population changes include Iitate Village, Minamisoma City, Katsurao Village, Kawamata Town, Kawauchi Village, Naraha Town, and Hirono Town. Except for Hirono, these municipalities are statistically identified as coldspots (Figure 5, in blue), meaning that low values are spatially clustered with statistical significance.

By contrast, from 2015 to 2020—after the evacuation orders were lifted—many of these coldspot municipalities experienced population increases. This is also confirmed by their identification as hotspots, where high values are spatially clustered. For example, between 2010 and 2015, population declined by 99.34% in Iitate, 98.82% in Katsurao, and 18.5% in Minamisoma. Between 2015 and 2020, population growth rates were 3,114% in Iitate, 2,233% in Katsurao, and 2.9% in Minamisoma. However, when looking at net population change from 2010 to 2020, Iitate saw a 78.8% decline, Katsurao 72.5%, and Minamisoma 16.8%. These figures show that the recovery in the latter period was limited and did not return to pre-disaster levels.

Kawamata Town, which was not entirely designated as an evacuation zone, experienced a less severe population decline from 2010 to 2015 compared to municipalities closer to the Fukushima Daiichi Nuclear Power Plant. However, no population recovery occurred between 2015 and 2020, and further decline was recorded (Figure 4). This indicates that even partially designated evacuation areas experienced significant long-term population decline.

In Figure 4, some areas lack population change data for the 2010–2015 period. These are difficult-to-return zones, where residential activities were restricted in principle (Reconstruction Agency, 2012). The absence of data implies nearly a 100% population loss, indicating the most severe depopulation. In addition to local effects, Fukushima Prefecture as a whole has shown a declining population trend. This may reflect both pre-existing aging and low birthrate trends and the broader demographic impact of the disaster.

On the other hand, the data reveal two municipalities—Otama Village and Nishigo Village—that experienced population growth. These municipalities share several common features: strong child-rearing support policies, rich natural environments, and convenient transportation access. Otama Village implemented free childcare services, subsidies for school lunch fees, free medical care for children, and childbirth and child-rearing grants. Nishigo Village also strengthened welfare policies, including medical expense subsidies for children (Otama Village, 2025; Nishigo Village, 2025). Located at the foot of Mt. Adatara and the Nasu Mountain Range, respectively, and adjacent to major cities such as Koriyama and Shirakawa with access to expressways and Shinkansen stations, these municipalities may have achieved unique demographic trends due to their policy successes and geographical advantages.

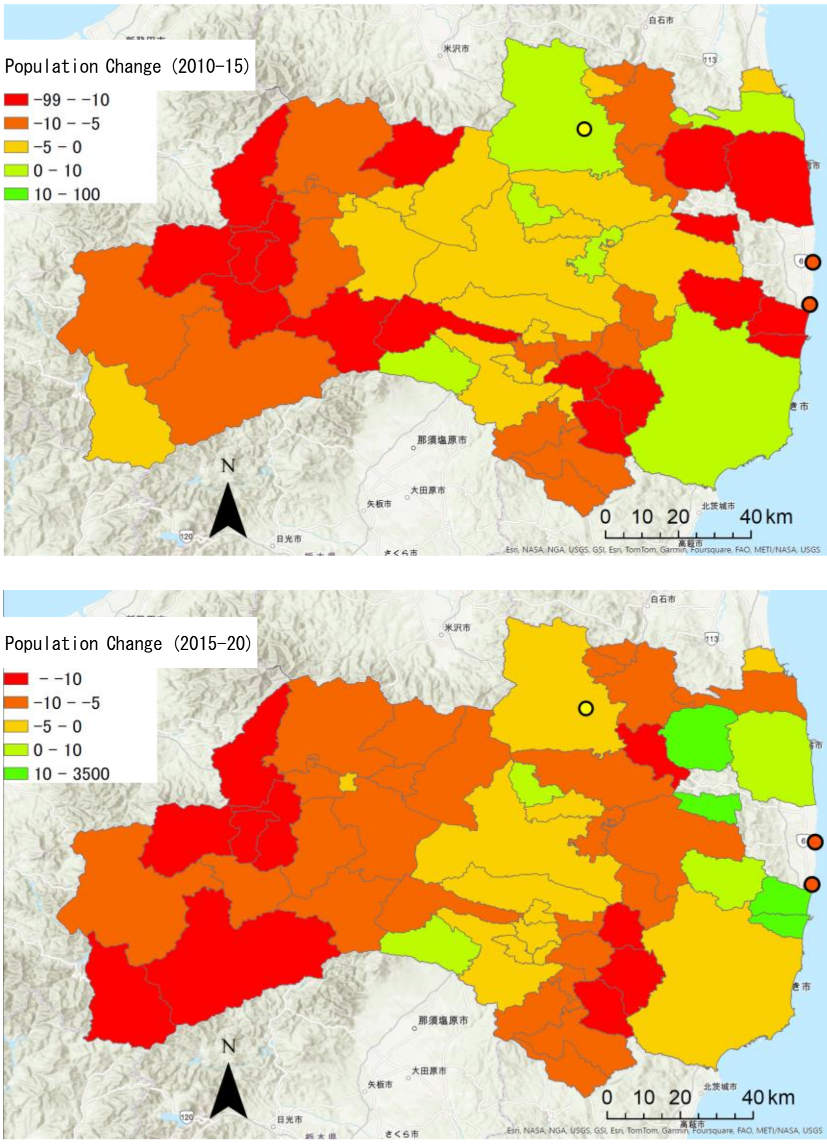

Figure 4. Population Change Rate (2010–2020)

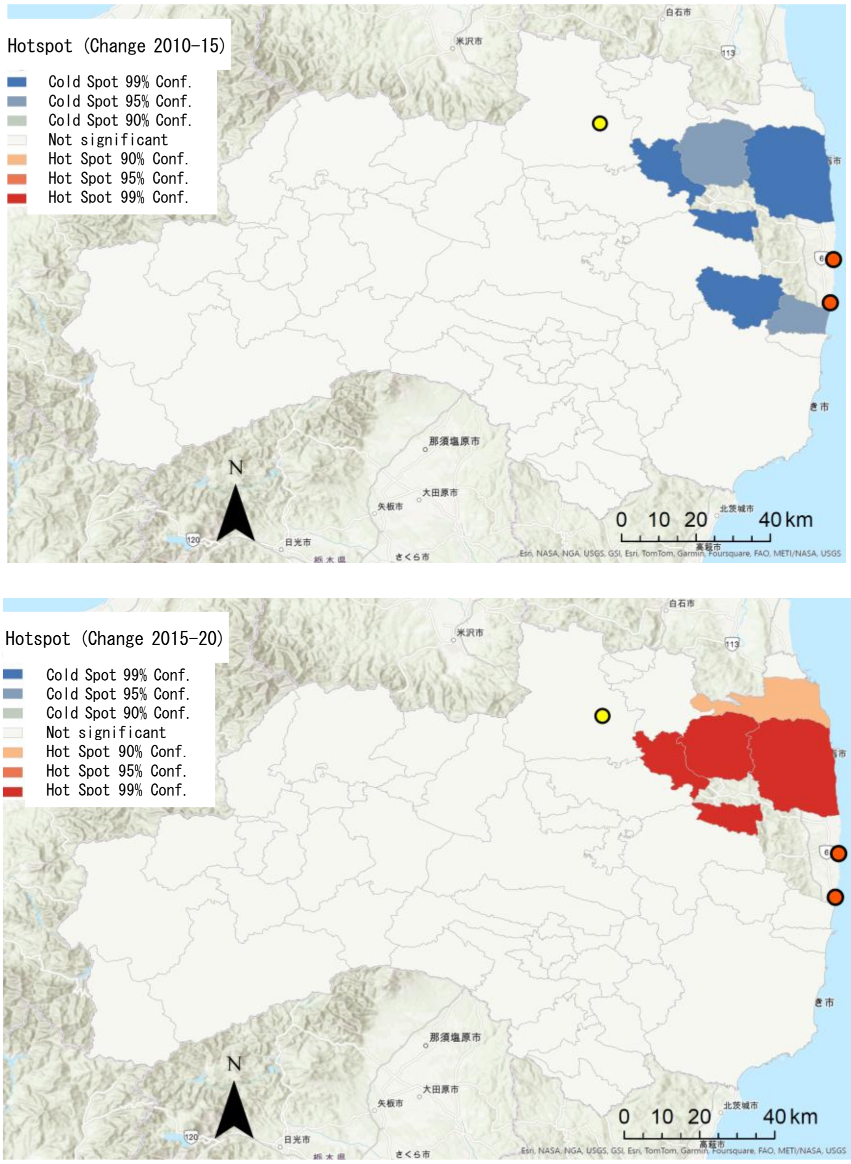

Figure 5. Hotspot Analysis of Population Change Rates (2010–2020)

To examine whether municipal revenue is associated with demographic trends, Figure 6 compares the fiscal conditions across regions using per capita general revenue—calculated by dividing total general municipal revenue by population—as an indicator. While this measure can become unstable in areas where evacuation orders caused sharp population declines, the total general revenue includes tax income, local allocation tax grants, and subsidies, making it a useful proxy for evaluating the financial capacity of local governments.

Notably, municipalities hosting nuclear power plants show significantly higher per capita revenue due to special grants provided under the so-called “Three Power Source Development Laws” (Federation of Electric Power Companies of Japan, 2025), reflecting a unique institutional background that differs from typical local fiscal systems[2].

Importantly, even in areas with high per capita revenue, there is no clear evidence of positive demographic effects such as population growth or increased immigration (see Appendix Figures 1 and 2). Instead, factors such as prolonged evacuation and the presence of difficult-to-return zones have exerted strong outward migration pressures. This suggests that abundant fiscal resources may not automatically lead to population retention or attraction.

Future analysis should focus on how these financial resources are allocated—specifically, which policy measures they support—and whether they contribute effectively to residents’ well-being and the reconstruction of local communities. A more detailed and quantitative evaluation of these outcomes is required.

[2] Appendix Figure 3 shows a fiscal index illustrating the ratio of revenue to expenditure in local governments.

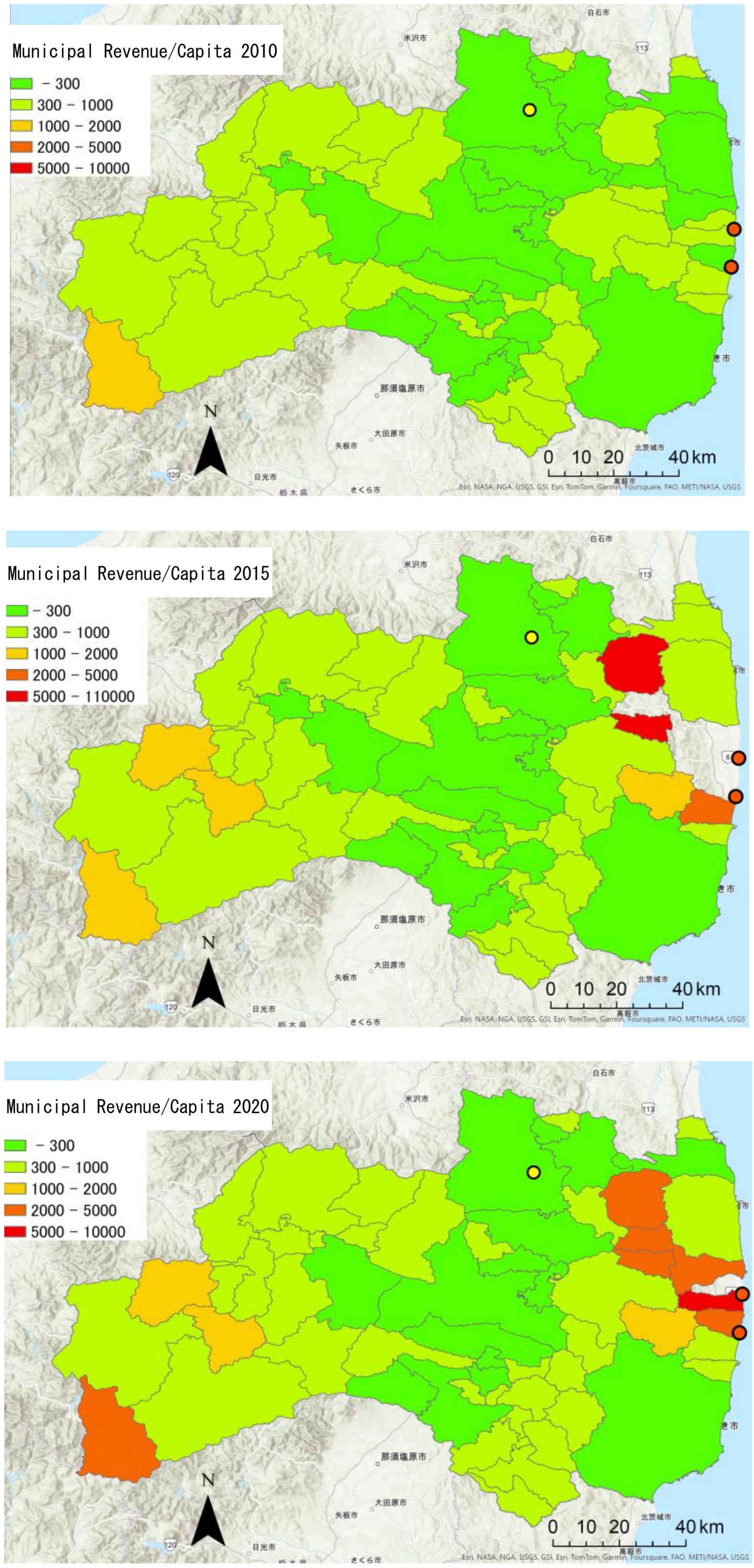

Figure 6. Per Capita General Revenue of Municipalities (2010–2020)

Considerations on Well-being Based on Spatial Data

We attempt to assess regional social inclusion and well-being in relation to demographic dynamics. However, the concepts of inclusion and well-being are multidimensional, consisting of components such as subjective well-being, sense of community belonging, and political participation. Micro-level data on these elements are extremely limited. In disaster-affected areas in particular, data collection is hindered by practical difficulties and sampling bias. Therefore, this study uses the number of deaths per capita (mortality rate) as a proxy variable.

Previous research has considered mortality rates as outcomes reflecting social support, poverty at the household and community levels, discrimination, and psychological distress or despair (Frandenberg et al., 2020; Case et al., 2022; Galea et al., 2011). These studies suggest that long-term health risks are influenced by social isolation, economic hardship, and the absence of support networks. For instance, Frandenberg et al. (2020) used more than ten years of longitudinal data to analyze mortality risks in Aceh, Indonesia, following the 2004 Indian Ocean tsunami. They found that mortality was significantly higher among elderly men with poor mental health and women who had lost their spouses, indicating that the breakdown of family and social networks has a serious impact on health outcomes. In contrast, Shigemoto et al. (2020) found that in areas affected by Hurricane Ike in the United States, psychological quality of life was significantly higher in communities with strong social cohesion, such as mutual trust and support among neighbors. This underscores the important role of community rebuilding and cohesion in psychological recovery after disasters, beyond institutional support alone.

On the other hand, demographic changes involving evacuation and relocation may also alter the age and household composition of communities, thereby affecting local mortality rates. Thus, while mortality cannot fully serve as a proxy for well-being, it can still offer meaningful insight in the absence of more comprehensive indicators—particularly as it reflects access to healthcare and social support. In our analysis, we also examined age distribution to account for compositional effects on mortality. In addition, we conducted econometric analysis using population change as the dependent variable and age structure as a control, drawing on available official statistical data to explore regional characteristics in the post-disaster context.

Figure 7 illustrates the spatial distribution of mortality rates (annual deaths per capita). In 2010, relatively high mortality was observed in the inland western areas of the prefecture. By 2015 and 2020, mortality rates had increased around the evacuation zones, likely linked to the sharp declines in resident population in those areas. These shifts may reflect broader changes in the social environment of disaster-affected regions.

Figure 8 presents the results of a hotspot analysis of mortality using the Getis-Ord Gi* statistic. In 2010, statistically significant positive spatial autocorrelation in mortality was observed in inland municipalities west of the Tohoku Shinkansen line—indicating hotspots in mountainous areas. After 2015, however, these hotspots shifted toward coastal municipalities adjacent to the evacuation zones, suggesting a transformation in the spatial structure of mortality risk. This shift appears to reflect demographic changes around the evacuation zones, rather than improvements in mortality in western areas.

Further insights can be gained by examining age distribution, as shown in Figures 9 and 10. High levels of ageing are not limited to areas near evacuation zones. Rather, the spatial pattern of aging is consistent across the study period: hotspots of aging are found west of the Aizu region (Figure 10), while areas along the Nakadori—including the Tohoku Expressway and Shinkansen line—tend to be coldspots. Between 2010 and 2020, the average age increased in nearly all municipalities except Nishigo Village, though the spatial distribution of age remained largely unchanged.

These findings suggest that changes in population and mortality in disaster-affected areas are not solely attributable to age structure. Instead, a variety of factors—including access to infrastructure, healthcare resources, social inclusion, and systems for daily living support—may influence regional disparities. Further detailed investigation is warranted.

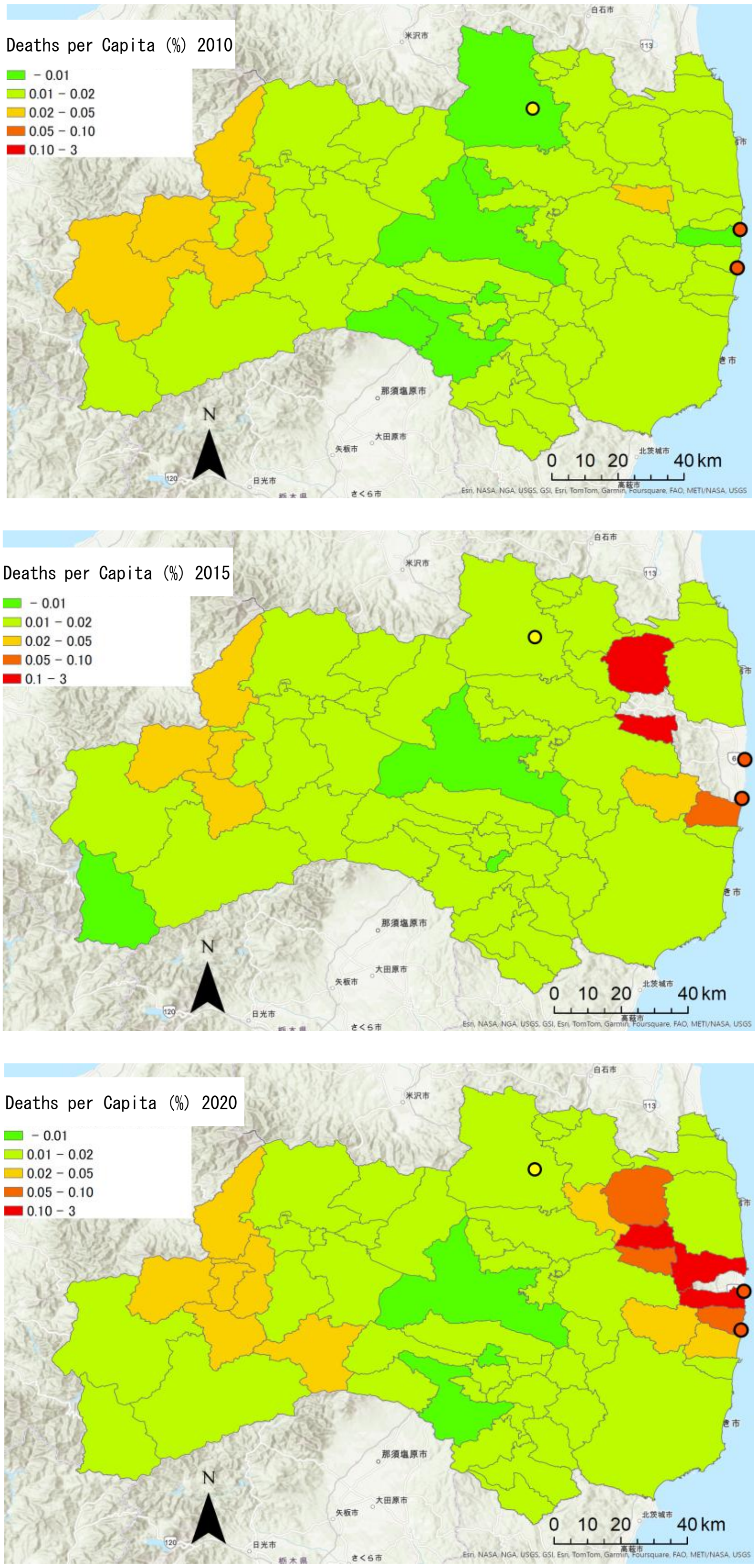

Figure 7. Number of Deaths per Capita (2010–2020)

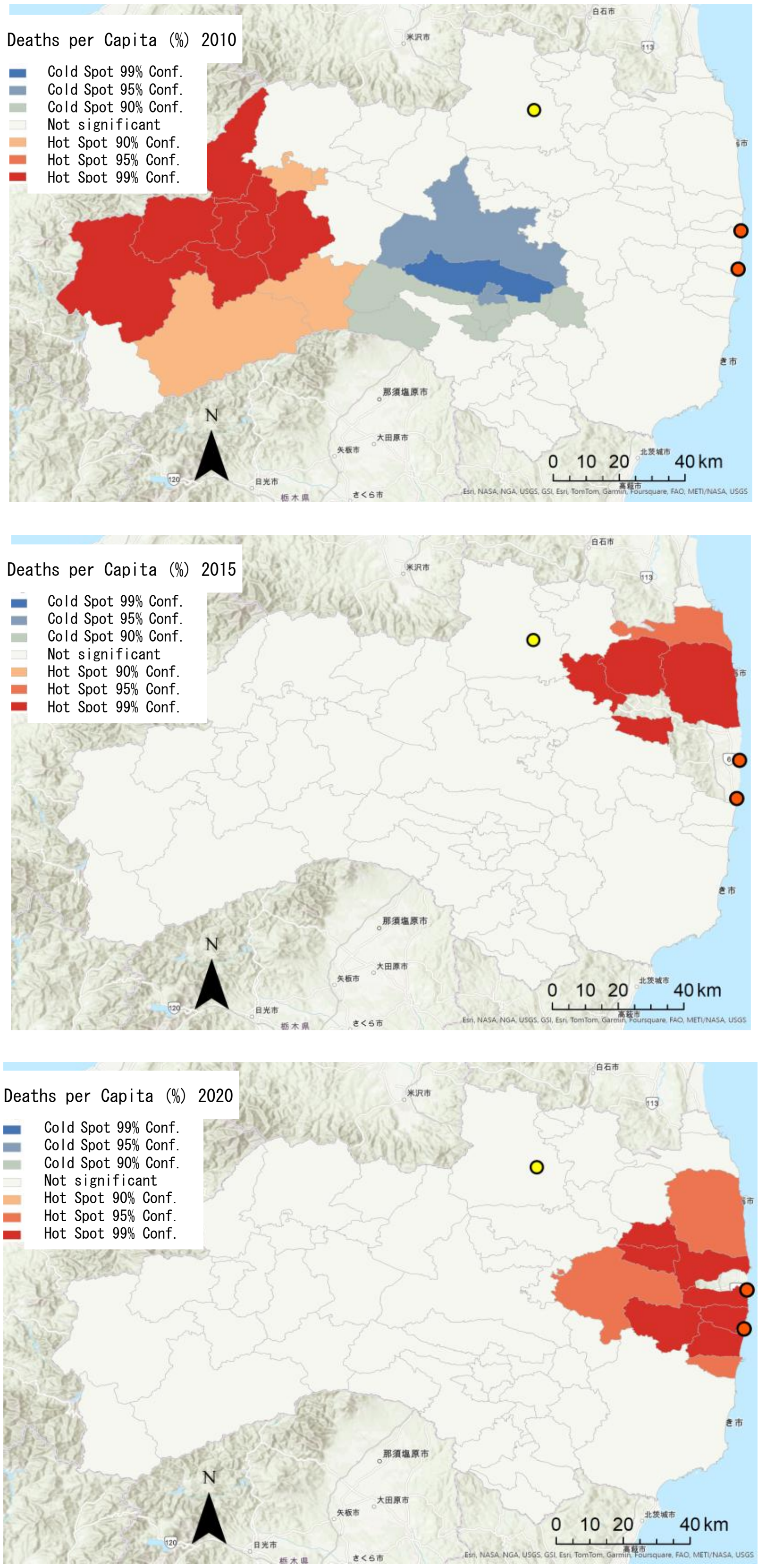

Figure 8. Hotspot Analysis of Deaths per Capita (2010–2020)

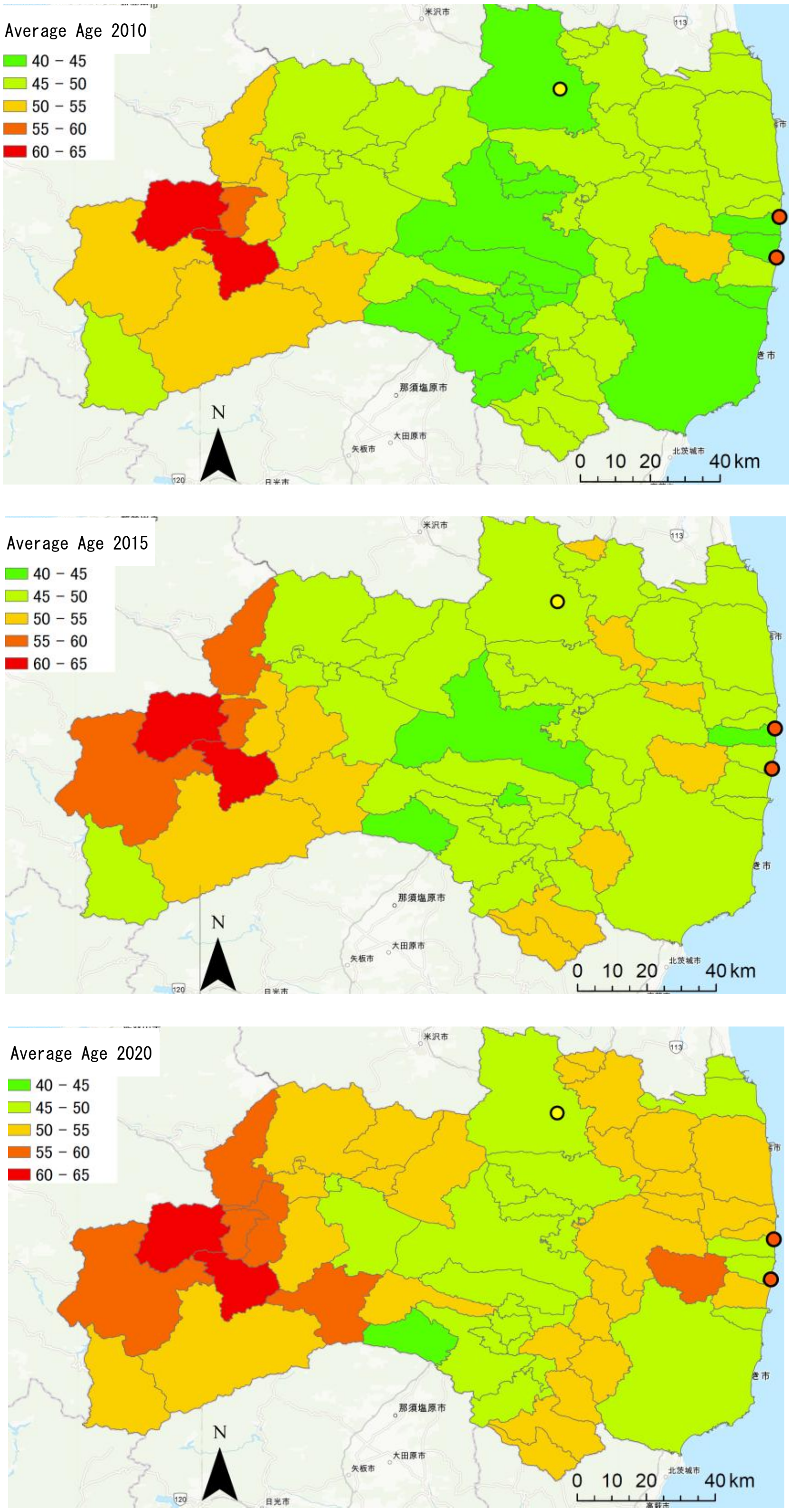

Figure 9. Average Age (2010–2020)

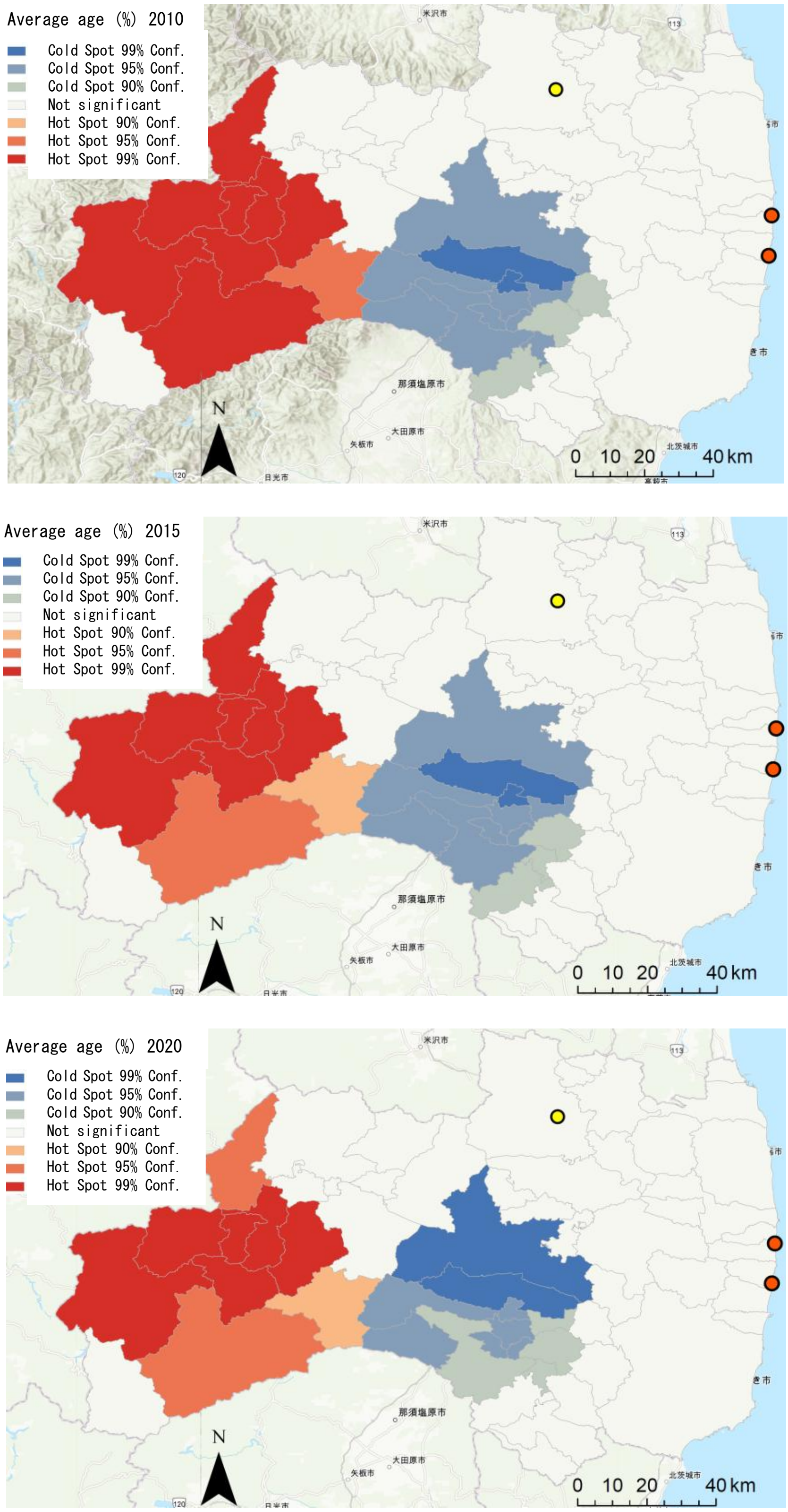

Figure 10. Hotspot Analysis of Average Age (2010–2020)

Econometric Analysis of Population Using Dynamic GMM

Finally, this section presents the results of a quantitative analysis examining the relationship between population change and other socioeconomic variables, using municipality-level panel data from 2010 to 2020. Table 1 shows the results of a Generalized Method of Moments (GMM) estimation, with population as the dependent variable and various socioeconomic and infrastructure-related variables as explanatory factors. The key findings are summarized below.

First, the coefficient for lagged population is −1.83 ($p = 0.028$), indicating a statistically significant negative effect. This suggests that municipalities with larger populations in the previous period tend to experience slower population growth in the following period. This may reflect stagnation in urban population growth or population increases in smaller municipalities. The coefficient for average age is −0.14 ($p = 0.035$), which is also statistically significant, suggesting that aging communities are more likely to experience population decline. This likely reflects population decreases due to lower birth rates and natural demographic decline.

In contrast, the fiscal capacity index shows a coefficient of −0.38 ($p = 0.778$), which is not statistically significant. This implies no clear relationship between a municipality's financial strength and short-term population changes. At least in this study, favorable fiscal conditions do not appear to directly influence residential preferences or migration of younger populations. Similarly, cultivated land areas show a small coefficient and a high p-value ($p = 0.453$), indicating no significant relationship between farmland area and population change.

Regarding infrastructure, the number of high schools (coefficient = 1.50, $p = 0.036$) and the number of hospitals (coefficient = 2.65, $p = 0.006$) both show statistically significant positive effects. Given the overall aging trend in Fukushima Prefecture, it is possible that well-developed educational and medical infrastructure contributed to population retention and slowed population decline.

Overall, the estimation results suggest that prior population levels and aging are major determinants of demographic change, while educational and healthcare infrastructure show a positive association with population maintenance. In contrast, fiscal indicators and agricultural resources do not appear to be significantly associated with population dynamics in the short term. Although this analysis is limited to municipality-level socioeconomic variables and is based on regression estimates—thus not establishing causal relationships—it implies that fiscal capacity alone may not have a direct effect, whereas investments in education and healthcare facilities could be more effective in mitigating population decline.

Table 1. Result for GMM

	Coef.	Std.	P-value
Lagged Population	-1.83	0.83	0.028
Average Age	-0.14	0.07	0.035
Fiscal Capacity Index (Municipal Finance)	-0.38	1.34	0.778
Cultivated Land Area (ha)	0.00	0.00	0.453
Number of High Schools	1.50	0.72	0.036
Number of Hospitals	2.65	0.96	0.006
Constant	7.18	3.66	0.049

Conclusion

This study serves as a first step in analyzing social inclusion by focusing on Fukushima Prefecture. It involved a review of prior research, the construction of a GIS-based demographic database, and econometric analyses to examine challenges related to social inclusion and demographic dynamics.

First, in the context of post-disaster recovery, economic compensation is positioned as a critical policy instrument. However, determining the amount and scope of compensation is highly complex. Research has shown that the compensation process itself can generate perceptions of unfairness, social comparison, and division, negatively affecting mental health. Even when monetary compensation is provided, it cannot fully address the loss of non-material resources and values. Nonetheless, prior studies have pointed out that monetary compensation tends to be the most widely requested form of support among affected residents, revealing a policy dilemma.

Building on these findings, this study analyzed regional demographic patterns using spatial statistical methods, specifically the Getis-Ord Gi* statistic to identify spatial autocorrelation. The distribution of geographic clusters (hotspots and coldspots) indicated statistically significant population decline and, to some extent, recovery in evacuation zones. However, overall population levels have not returned to their pre-disaster levels. In 2010, high mortality hotspots were concentrated in the aging inland western region. By 2015, these clusters had shifted to coastal areas adjacent to the evacuation zones. This change suggests significant population decline and compositional shifts in these areas. Meanwhile, the spatial distribution of aging remained largely unchanged before and after the disaster, with aging hotspots consistently concentrated west of the Aizu region. This implies that aging is driven more by structural and geographic factors than by disaster-related spatial relocation.

The analysis also suggests that, beyond aging, other factors—such as physical infrastructure, access to healthcare, and the inclusiveness of local support systems—may have contributed to elevated mortality rates.

Finally, the econometric analysis employed a dynamic GMM model with population as the dependent variable to examine relationships with prior population levels, aging, and social infrastructure. The estimation results showed a significant negative effect of lagged population, indicating a convergence tendency in population levels. Increases in average age had a significant negative effect on population, reflecting demographic decline through natural decrease. In contrast, indicators of social infrastructure, such as the number of hospitals and high schools, had a positive and statistically significant association with population levels, suggesting their contribution to population retention. However, fiscal indicators did not show statistically significant associations.

In Fukushima's disaster-affected areas, major shifts in population dynamics were observed. Before 2010, aging and depopulation in mountainous areas were already pressing issues. These challenges remained unresolved, while new challenges emerged in evacuation-designated zones. Prior research has shown that direct financial assistance can sometimes generate conflict and that community connectedness—an essential aspect of inclusion—is positively associated with mental health. This study similarly suggests that fiscal autonomy or surplus alone does not necessarily influence population growth or reductions in mortality. Instead, the appropriate allocation of healthcare and educational infrastructure, along with social support systems, is likely to play a key role in maintaining population and revitalizing communities in the post-disaster context.

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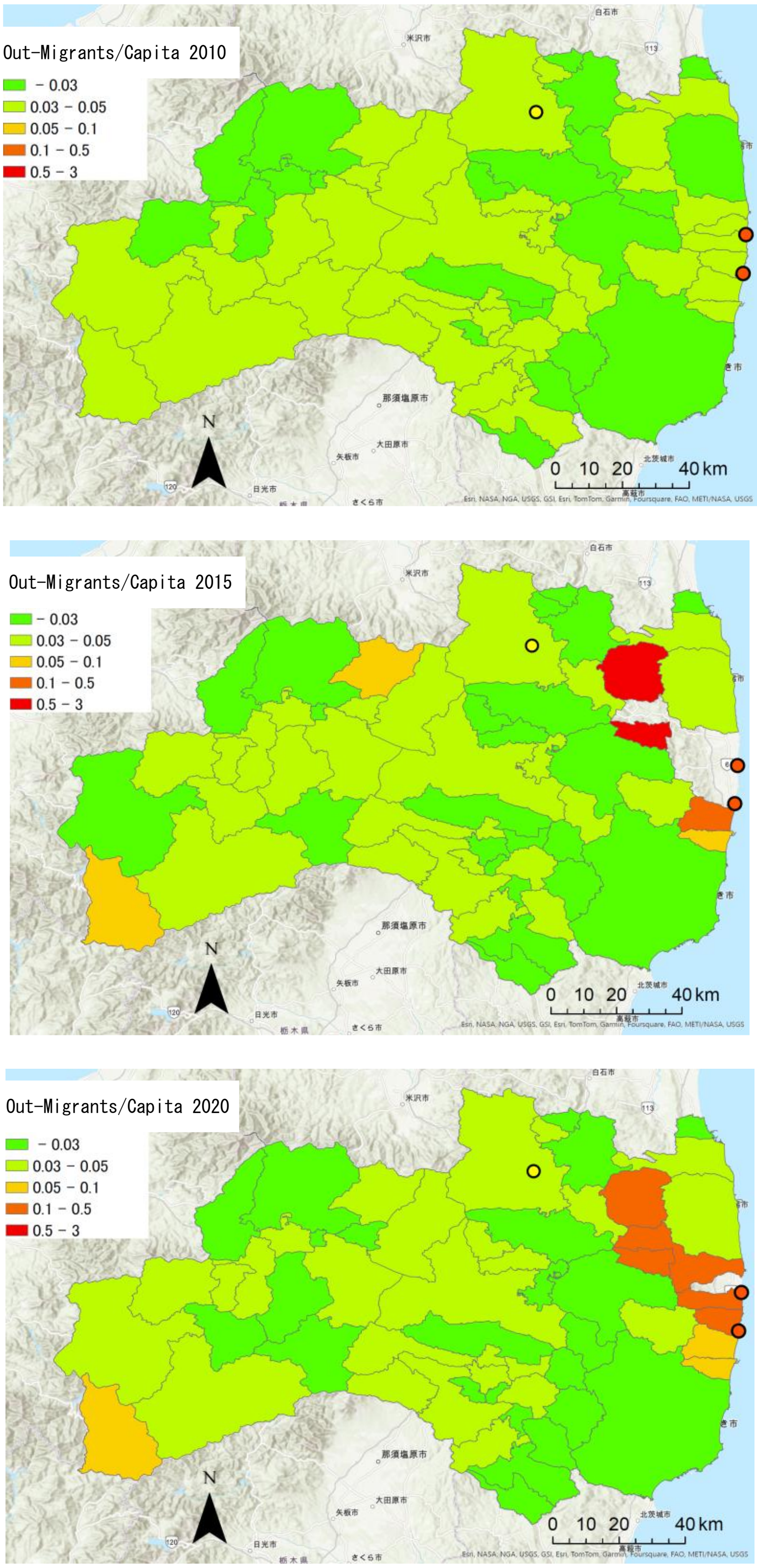
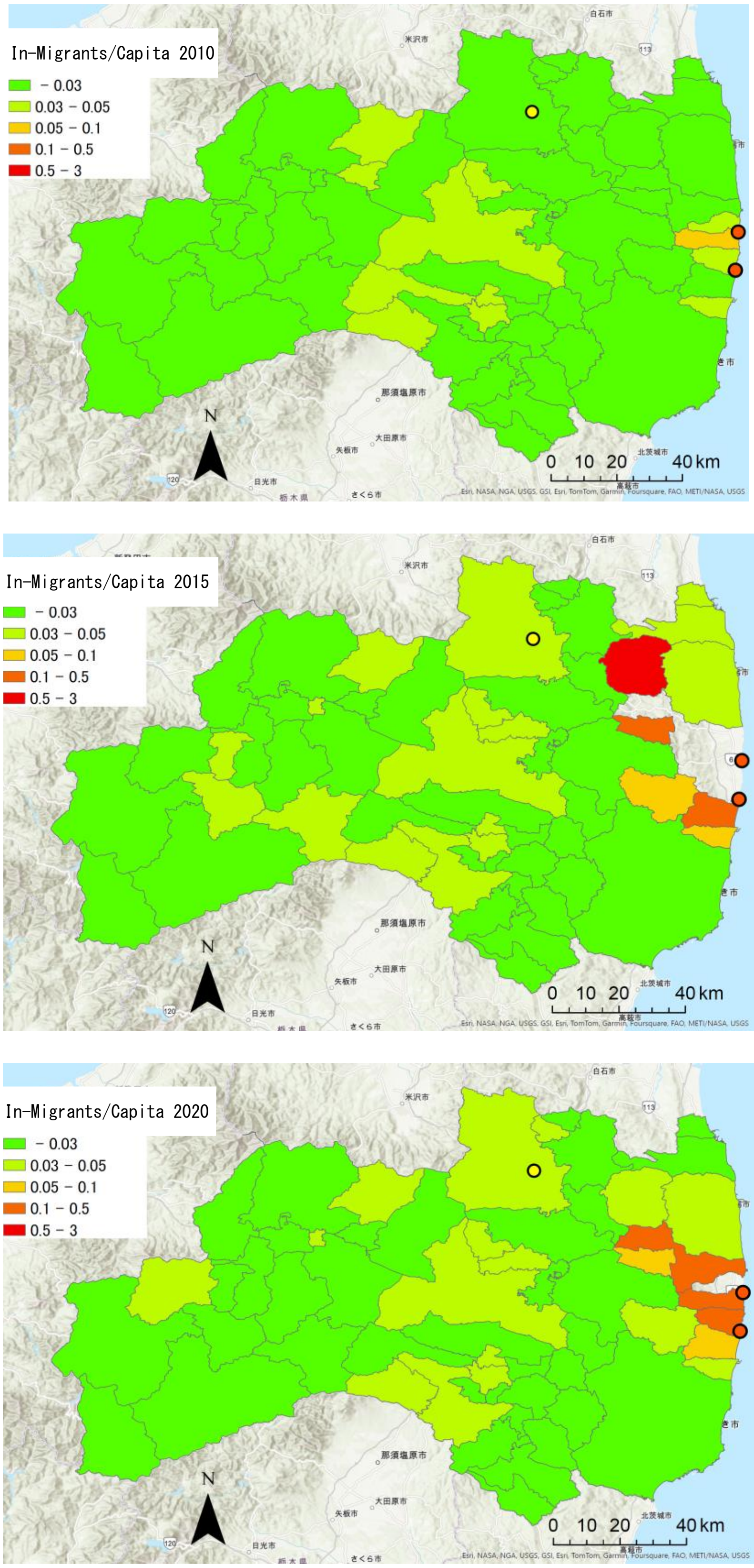
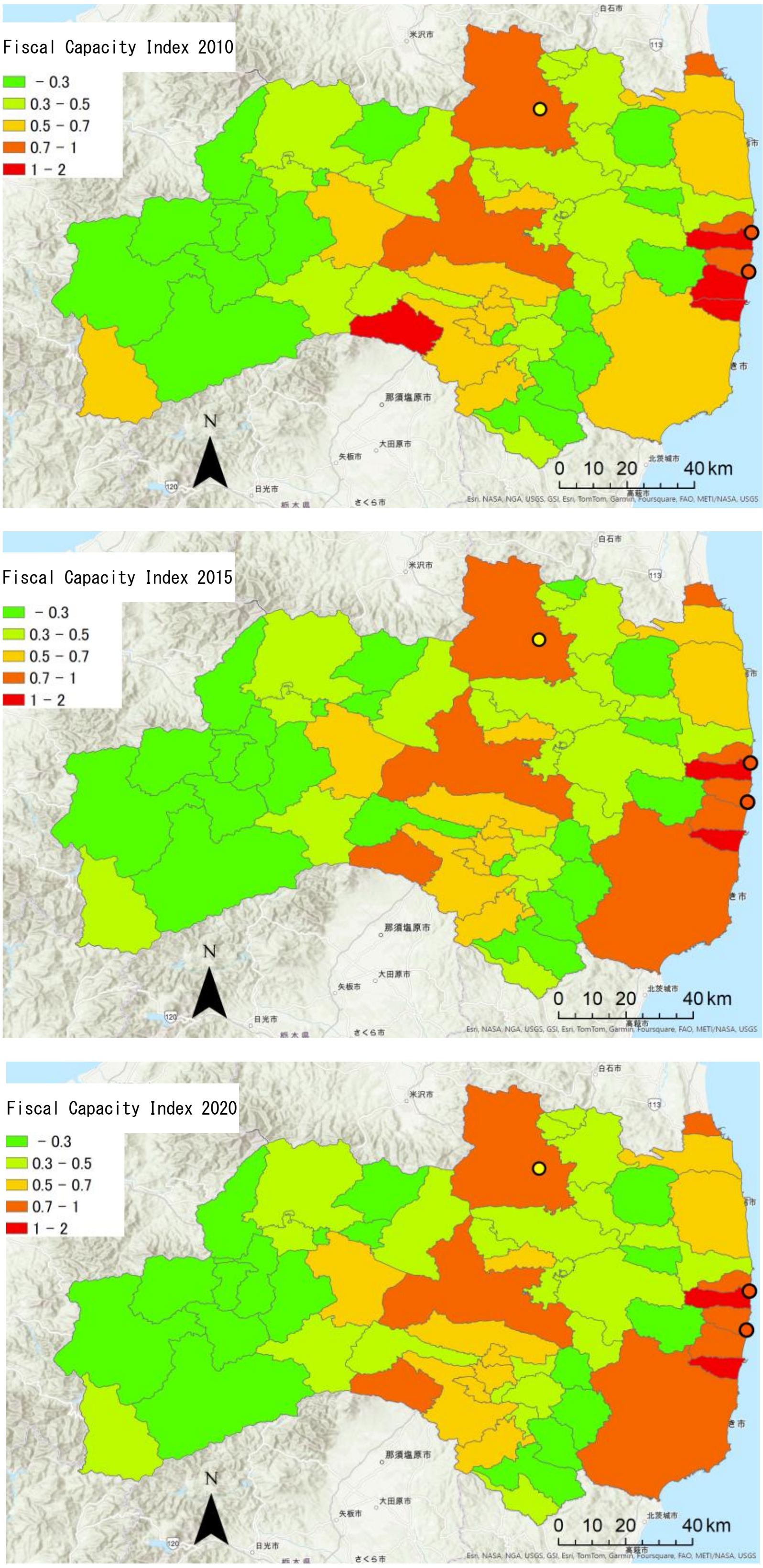
Appendix



Appendix Figure 1. Number of Out-Migrants (2010–2020)



Appendix Figure 2. Number of In-Migrants (2010–2020)



Appendix Figure 3. Fiscal Capacity Index (2010–2020)